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Intelligent Monitoring of Smoking Prohibition in Public Spaces Using YOLOv8: Real-Time Detection and Telegram Notifications

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Abstract: This study aims to develop an intelligent monitoring system that supports the enforcement of smoking prohibition in public spaces by leveraging advancements in Artificial Intelligence (AI) and deep learning. Utilizing the YOLOv8 (You Only Look Once version 8) object detection model, the system is designed to identify smoking activities in real-time and promptly send alerts through the Telegram messaging platform. The proposed method integrates real-time object detection with an automated notification system, ensuring responsive enforcement across diverse environmental conditions, including normal lighting, low-light scenarios, and partially occluded views. The system architecture combines the YOLOv8 model for detection and a Python-based Telegram bot for communication. The model was evaluated using a test dataset collected from various public spaces. It achieved an F1-Score of 81% and a confusion matrix accuracy of 89%, indicating a high level of reliability and precision in identifying smoking behaviors. Additionally, the average notification response time via Telegram was 1.5 seconds, enabling near-instantaneous alerting for enforcement personnel. In conclusion, the results demonstrate that the system is both accurate and efficient in detecting smoking activities. Its robust performance across different conditions and rapid alert mechanism positions it as a practical and scalable solution to enhance compliance with smoking regulations in public areas.

Keywords: Artificial intelligence; Confusion matrix; Deep learning; Object detection; Real-time monitoring; Smoking detection; Telegram notification; YOLOv8

Introduction

Smoking in public spaces has long been a global concern, posing detrimental effects on public health and environmental quality (Halim et al., 2022; Yang et al., 2023). Exposure to cigarette smoke not only endangers active smokers but also presents serious health risks to passive smokers—particularly vulnerable groups such as children, the elderly, and individuals with specific health conditions (Liu et al., 2024; Yunarman et al., 2020; Basri et al., 2023). These risks have prompted many countries (Singapore, Canada, and Australia) to implement strict regulations banning smoking in public spaces (Teed et al., 2024; Indra et al., 2023). However, the enforcement of these regulations continues to face significant challenges. Traditional manual monitoring methods, which depend heavily on field personnel, suffer from limited coverage, inconsistent enforcement, and high operational costs (Muslim et al., 2023). Violations often go unnoticed unless reported by the

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public, which delays enforcement actions and weakens the deterrent effect of the regulations (Rachmawati et al., 2024). This creates a gap between policy and practice, undermining public trust and reducing the effectiveness of smoke-free zone implementation. In light of these limitations, there is a clear and urgent need for a more effective, efficient, and responsive monitoring mechanism (Ulfah et al., 2024). This need aligns with broader public health goals and supports the creation of safer, healthier environments in shared community spaces (Yan Li et al., 2024; Terven et al., 2023; Wang et al., 2024).

Recent advancements in artificial intelligence (AI), particularly in the field of deep learning, offer powerful tools to bridge this gap (Paramita et al., 2024). Object detection technology based on deep learning models has emerged as a promising solution (Saputra et al., 2024). Among them, the YOLO (You Only Look Once) series has gained recognition for its ability to detect objects rapidly and accurately in real-time. Its latest version, YOLOv8, provides enhanced performance with superior detection accuracy and adaptability in diverse and complex environmental conditions (Ilić, 2024). This makes it especially suitable for real-time detection of smoking behaviors in dynamic public spaces, such as transportation hubs, parks, and commercial areas (Park & Lee, 2024; Terven et al., 2023; J. Zhang et al., 2023; W. Zhang et al., 2024).

This study proposes the development of an intelligent monitoring system using YOLOv8, integrated with Telegram-based notification capabilities, to detect and report smoking activity in real-time (Putri et al., 2025). By utilizing video feeds from surveillance cameras, the system operates autonomously to identify smoking behavior and immediately notify authorities or responsible personnel via Telegram (Arirul et al., 2024). This approach enables rapid response, minimizes the need for constant human supervision, and significantly reduces labor costs (Yao et al., 2024). The novelty of this research lies in the real-time integration of an advanced deep learning model (YOLOv8) with a communication platform for automated law enforcement. In contrast to previous studies that focused solely on detection accuracy, this system demonstrates both technical robustness and real-world applicability with a proven response time of only 1.5 seconds.

What makes this research particularly important is its contribution to public policy enforcement through technology (Astiadewi et al., 2025; Diharja et al., 2022). By replacing or supporting manual monitoring systems, this AI-based solution addresses key enforcement gaps while promoting compliance (Nugroho et al., 2024; Immanuel et al., 2024). The instant notification mechanism also strengthens the responsiveness of enforcement, increasing the deterrent effect on potential violators. In the long term, this can lead to greater public adherence to smoking regulations, improved air quality, and a better quality of life for the general public (Yuliswar et al., 2025). Moreover, this research provides a scalable and replicable model for future implementations, both locally and globally. Its findings are expected to inspire further development of intelligent surveillance systems aimed at addressing other forms of public misconduct or health-related regulations. In summary, this study not only demonstrates the feasibility of using advanced AI models for regulatory enforcement but also highlights their transformative potential in enhancing public health infrastructure and societal well-being (Chetoui & Akhloufi, 2024).

It provides new insights into how the combination of deep learning and real-time communication tools can be effectively deployed to support smoke-free environments. This integration also sets a foundation for broader innovations in smart surveillance and health-oriented technologies.

Method

In this study, a YOLOv8-based smoking activity monitoring system was designed to detect violations of smoking prohibitions in public spaces in real-time and provide instant notifications to authorities via the Telegram platform. The methodology consists of three main stages: system design, data processing, and model performance evaluation (Noor et al., 2023; Kurniawan et al., 2023; Gozali, 2023). The methodology for the smoking detection model is illustrated in Figure 1.

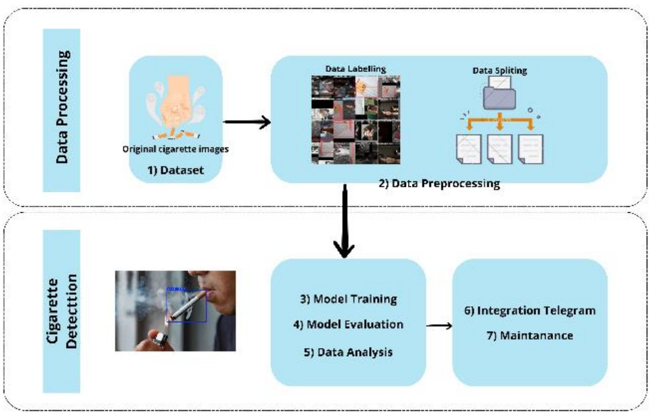


Figure 1. Methodology for smoking detection in public spaces

System Design

The system comprises several key components that work integrally to detect smoking activities in public areas. The first component is a surveillance camera, which records real-time video in monitored areas such as public spaces or designated no-smoking zones. This video serves as the input for the smoking activity detection process (Islami et al., 2024). The recorded video is sent to a processing device—either an edge device or a server with GPU support (e.g., NVIDIA RTX 3060, 16 GB RAM)—that runs the YOLOv8 model. YOLOv8, as an object detection model, is utilized to identify indicators of smoking activities, such as individuals holding cigarettes (Yiting Li et al., 2023; Park & Lee, 2024; Rahman et al., 2024).

Once a smoking activity is detected, the system automatically sends a notification to the authorities via Telegram. The Telegram bot was developed using the Telegram Bot API and integrated via Python scripts and webhook functions to ensure low latency and reliable delivery. With the integration of all these components, the system is expected to support the enforcement of smoking prohibition regulations in monitored areas. The system design is illustrated in Figure 2.

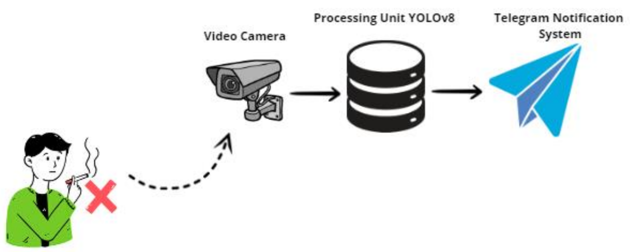


Figure 2. System design for telegram notifications in smoking activity detection

Data Processing

The data processing stage is a critical component in the development of the smoking activity detection model, encompassing data collection, pre-processing, and training of the YOLOv8 (Zhao et al., 2022). The following outlines the detailed steps involved:

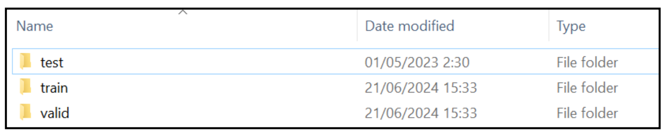
Data Collection

Figure 3. Sample images from the dataset

The dataset used consists of a collection of relevant images and videos illustrating smoking activities, such as individuals holding cigarettes or exhaling smoke (Muttaqin & Sudiana, 2025). Figure 3 illustrates representative images of individuals smoking, captured from public domains and direct field recordings. Data collection was conducted from various public sources as well as direct recordings to ensure sufficient data diversity. This variation ensures the model is robust under different lighting, viewing angles, and crowded backgrounds (Casas et al., 2023).

Data Preprocessing

The collected data, totaling 742 images, underwent further processing to align with the YOLOv8 model requirements Annotation was done using LabelImg, where each object related to smoking was labeled with bounding boxes, and results saved in YOLO format (.txt). Data augmentation was then applied to enhance sample diversity using techniques such as rotation, lighting adjustments, scaling, and object position shifting. This step increases the generalizability of the model to various real-world conditions. Finally, the dataset was proportionally divided into three main sets, as illustrated in Figure 4: 64% for the training set, 21% for the validation set, and 15% for the testing set. The dataset folder structure complies with YOLOv8 requirements, including the use of a data.yaml configuration file.



Name	Date modified	Type
test	01/05/2023 2:30	File folder
train	21/06/2024 15:33	File folder
valid	21/06/2024 15:33	File folder

Figure 4. Data division

The Figure 4 illustrates the folder structure resulting from the data preprocessing stage, which is a crucial step before training the YOLOv8 model. During this process, raw image data is organized into three main subsets: train, valid, and test. The train folder contains the majority of the images and corresponding annotation files used to train the model. The valid folder includes a smaller portion of the dataset to validate the model's performance during training and ensure that it generalizes well. The test folder holds unseen data, which is used after training to evaluate the final performance of the model in real-world scenarios. This structured separation of data ensures that the model is trained and evaluated fairly, avoids data leakage, and follows standard practices in machine learning workflows. The folder timestamps indicate when the data was last modified, confirming the timeline of dataset preparation. This preprocessing stage involved image annotation (e.g., using tools like LabelImg or

Roboflow), data splitting, and organizing files into the appropriate directories to comply with YOLOv8's input format requirements.

Training the YOLOv8 Model

After preprocessing, the YOLOv8 model was trained using the processed data to accurately recognize smoking activities. The model was trained using Python with the Ultralytics YOLOv8 library (PyTorch-based). The training process involved optimizing various parameters, such as the learning rate to balance convergence speed and stability, the number of epochs (200 epochs in this case) to allow the model to repeatedly observe the entire dataset, and the batch size for efficient memory utilization (Terven et al., 2023). All these steps are intended to enable the YOLOv8 model to detect smoking activities with a high level of accuracy under various operational conditions. The training process for the YOLOv8 model is illustrated in Figure 5.

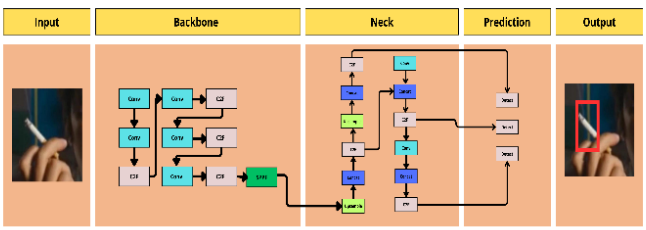


Figure 5. Training of the YOLOv8 model

Model Performance Evaluation

A confusion matrix is a table used to evaluate the performance of a classification model by comparing the model's predicted outcomes with the actual values of the test data (Hayati et al., 2023). The table consists of four sections that represent the four possible outcomes of the classification process: True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN).

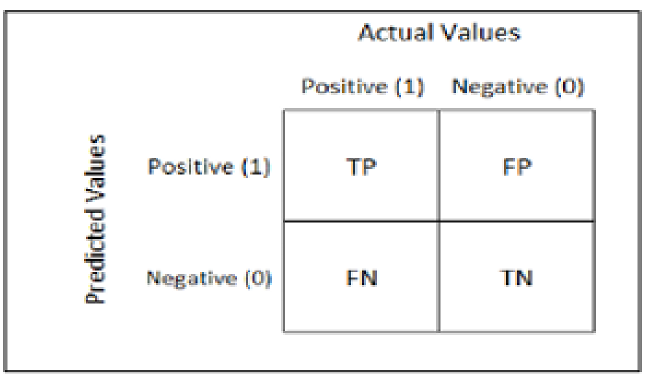


Figure 6. Confusion matrix

From the confusion matrix shown in Figure 6, several evaluation metrics can be calculated:

a. Accuracy, indicates how often the predictions are correct, calculated using the formula:

$$Accuracy = \frac{TP + TN}{TP+TN+FP+FN} \quad (1)$$

b. Precision, the proportion of correctly identified positive detections out of all positive predictions, calculated as:

$$Precision = \frac{True\ Positive}{Actual\ Result} = \frac{TP}{TP+FP} \quad (2)$$

c. Recall, The proportion of correctly predicted positive instances out of all truly positive samples, calculated using the formula:

$$Recall = \frac{True\ Positive}{Predicted\ Result} = \frac{TP}{TP+FP} \quad (3)$$

d. F1-Score, The harmonic mean of precision and recall, calculated using the equation:

$$Score = 2\,x \frac{Precision * Recall}{Precision+Recall} \quad (4)$$

Testing and Data Analysis

Testing and data analysis were conducted to evaluate the performance of the smoking activity detection system in real-world conditions. Three cameras were deployed across designated no-smoking areas at different times of day. Field testing was carried out in public areas with varying lighting and crowd conditions. Surveillance cameras recorded video, which was analyzed by the YOLOv8 model to detect smoking activities. Detection accuracy was measured using precision, recall, and F1-Score metrics, while system latency was measured to ensure a quick response time in sending notifications to the authorities (Santos et al., 2022). Authorities received real-time notifications via Telegram, and provided feedback indicating satisfactory system performance. Some false positives (e.g., people holding pens or straws) were identified, which were addressed by adjusting training data and thresholds. The testing results were analyzed to identify limitations, such as false positives and false negatives, as well as factors that affect the model's performance. Feedback from authorities was also taken into account to assess detection accuracy (Jiang et al., 2021; Sukardjo et al., 2023). Based on this analysis, the model was refined to improve both accuracy and efficiency. This evaluation aims to ensure the system's reliability in enforcing smoking prohibition regulations in public spaces and to provide recommendations for further development.

Telegram Integration

Integrating Telegram into the smoking activity detection system allows real-time notifications to be sent to authorities whenever a violation is detected. The Telegram bot was created using BotFather and connected to the system via an API token to enable automated message delivery (Nasution & Kartika, 2022). When the YOLOv8 model detects smoking activity, the bot sends a notification containing important information such as the time and location of the event. Testing was conducted to ensure that the messages are sent with low latency and are consistently received. This integration ensures that authorities can respond to violations quickly and efficiently. The Telegram token is shown in Figure 7.

```
from telegram import Bot
from telegram.ext import Updater, MessageHandler
from telegram.ext.filters import Filters

telegram_token = '7340055791:AAFKukw2GuDRpqsz[redacted]

def get_chat_id(update, context):
    chat_id = update.message.chat_id
    print(f'Your chat ID: {chat_id}')
    context.bot.send_message(chat_id=chat_id, text=f'Your chat ID: {chat_id}')

updater = Updater(token=telegram_token, use_context=True)
dispatcher = updater.dispatcher
dispatcher.add_handler(MessageHandler(Filters.text & ~Filters.command, get_chat_id))

updater.start_polling()
updater.idle()
```

Figure 7. Telegram token

Result and Discussion

This section presents a comprehensive analysis of the results obtained from testing and implementing a YOLOv8-based monitoring system designed to detect smoking activities in public areas (Yang et al., 2023). The discussion focuses on evaluating the system's detection accuracy, response speed, and overall performance in recognizing violations of smoking regulations. The system's behavior is examined both in controlled testing environments and in real-world field conditions to assess its practical applicability and robustness. Furthermore, comparisons with relevant previous studies are included to strengthen the reliability and relevance of the findings, as well as to highlight the technological advancements and limitations observed throughout the development and deployment process.

Smoking Activity Detection Result

During the testing phase, the YOLOv8 model demonstrated a strong capability in accurately detecting smoking activities. The system was able to reliably identify visual elements associated with smoking behavior—particularly cigarettes—with a high degree of precision. It successfully detected violations within a reasonable timeframe, supporting its effectiveness for real-time monitoring purposes. However, the system encountered certain limitations, especially under suboptimal conditions such as low lighting or when the smoking object was partially obstructed from view, which slightly affected detection performance.

As illustrated in Figure 8, the YOLOv8 model successfully detected cigarettes in a controlled indoor setting. Two cigarette objects are detected, each marked with a red bounding box labeled "rokok" (Indonesian for "cigarette"), and assigned confidence scores of 0.28 and 0.34, respectively. These confidence scores reflect the model's certainty in identifying the objects as cigarettes. The environment in which the detection was carried out features consistent lighting and minimal background interference, enabling the model to focus more precisely on the target objects. This example reflects the system's competence in identifying cigarette objects in static and predictable environments, which is essential for calibration and further refinement of detection accuracy in more complex scenarios.

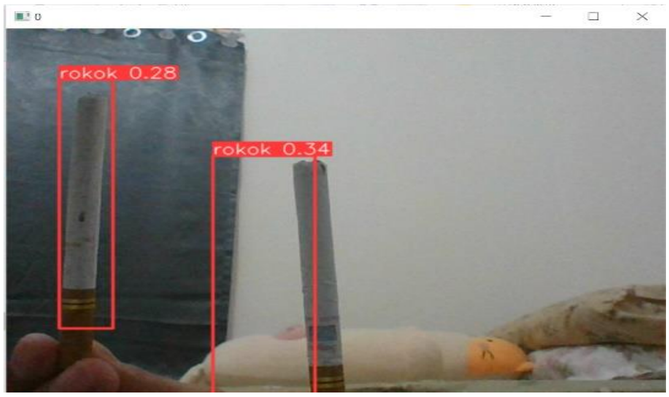


Figure 8. Detection in normal environment

Model Performance Evaluation

The YOLOv8 model was trained using cigarette images over the course of 200 epochs, with each image resized to 640×640 pixels. Throughout the training process, the model's performance was continuously evaluated using key metrics including precision, recall, and mean Average Precision (mAP), as summarized in Table 1.

Table 1. Model Training Results

Epoch	Precision	Recall	mAP
40/200	0.735	0.832	0.464
80/200	0.754	0.854	0.475
120/200	0.743	0.865	0.456
160/200	0.787	0.875	0.565
200/200	0.846	0.886	0.532

At the conclusion of the training phase, the model achieved a validation precision of 0.773, recall of 0.862, and an average mAP of 0.498. These values indicate that the model maintained a balanced ability to correctly identify smoking-related objects while minimizing false negatives and false positives. To further quantify model performance, the F1-Score was calculated as follows:

$$\text{F1 } Score = 2\,x\,\frac{Precision\;x\;Recall}{Precision + Recall} = 2\,x\,\frac{0{,}773 * 0{,}862}{0{,}773 + 0{,}862} = \frac{1.332}{1{,}635} = 81\%$$

This F1-Score confirms the model's robustness in maintaining both high precision and high recall simultaneously.

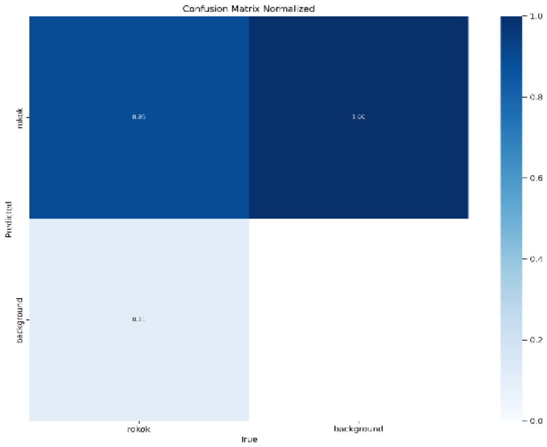


Figure 9. Confusion matrix

The confusion matrix depicted in Figure 9 further supports the evaluation results, showing that 89% of cigarette objects were correctly classified as such (True Positive rate), while 11% were either misclassified as background or missed entirely. This performance is considered strong, especially given the real-time constraints and visual complexity involved in public space surveillance.

Figure 10 illustrates the training progression of the model, displaying trends across several performance indicators. A consistent decline in box loss, classification loss, and objectness loss suggests the model's increasing ability to make accurate predictions. Additionally, the precision, recall, and mAP curves demonstrate upward trajectories throughout the training epochs. These trends collectively indicate that the training process successfully enhanced the model's ability to detect and localize cigarette objects with growing accuracy and reliability over time.

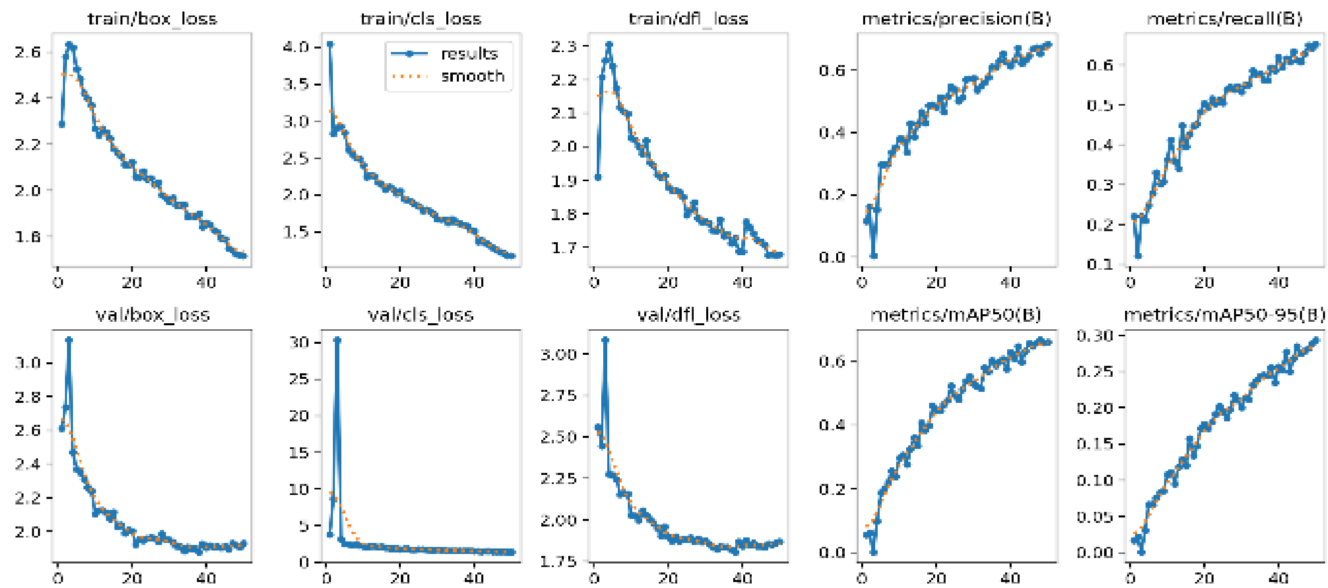


Figure 10. Graphical results

Response Time and Telegram Notifications

The monitoring system's responsiveness was evaluated based on its ability to detect violations and deliver real-time alerts via Telegram. Upon detection of a cigarette by the YOLOv8 model, the system was designed to instantly capture the detected frame, annotate it with bounding boxes and confidence scores, and forward it to a designated Telegram bot.

Table 2 presents the response time for sending notifications to Telegram after detecting cigarettes. The table includes two columns: "Detection," which shows the detected object (in this case, "Cigarette" for each row), and "Timestamp," which indicates the response time in seconds. The recorded response times are 1.445 seconds, 1.654 seconds, 1.564 seconds, 1.678 seconds, and 1.234 seconds, indicating that the system can send alerts with low latency, generally within approximately 1.5 seconds. This show the efficiency of the system in sending real-time notifications to authorities when smoking activity is detected.

Table 2. Telegram Response Time

Detection	Timestamp
Cigarette	1.445 seconds
Cigarette	1.654 seconds
Cigarette	1.564 seconds
Cigarette	1.678 seconds
Cigarette	1.234 seconds

Figure 11. Real-time telegram notification

Figure 11 shows an example of a Telegram notification received from the monitoring system. The image clearly displays the annotated cigarette with a confidence label, providing both visual proof and metadata (such as time and location) if integrated. This feature enables authorities or system operators to act promptly upon receiving the alert.

Field Testing

Following the successful implementation and evaluation of the system in a controlled environment, field testing was conducted to assess its performance under real-world conditions. The results revealed that the system maintained a strong ability to detect smoking activities, even in crowded public areas. However, certain external factors were found to impact detection accuracy. Visual obstructions—such as individuals standing too close to the camera, objects partially blocking the view, or complex background elements—occasionally hindered the system's ability to identify cigarettes correctly. Despite these challenges, the system consistently demonstrated reliable performance in identifying violations promptly. The outcomes suggest that while the detection model is generally robust, its effectiveness could be further improved through enhanced image processing techniques or strategic camera placement to minimize obstructions in practical deployments.

Figure 12. Field testing results

Discussions

The findings of this study highlight the strong potential of integrating advanced artificial intelligence technologies—specifically the YOLOv8 object detection model—into public space monitoring systems. This integration enables real-time detection of smoking activities and immediate notifications to relevant authorities, demonstrating the practicality of deep learning in supporting regulatory enforcement. YOLOv8's advanced features, including its anchor-free architecture and improved feature extraction capabilities, offer significantly higher accuracy in complex environments compared to previous versions like YOLOv3 and YOLOv4 (Wang et al., 2024). The system developed in this study achieved an F1-Score of 81% and a confusion matrix accuracy of 89%, indicating reliable performance with high levels of precision and recall. Supporting studies by Wang et al. (2023) have further validated YOLOv8's effectiveness in dynamic real-world settings such as industrial zones and crowded public areas, highlighting the model's scalability and adaptability.

Moreover, this system overcomes key challenges commonly faced by earlier models, such as difficulties in detecting objects in low-light conditions or when partially obscured—issues previously noted in studies involving YOLOv4 (W. Zhang et al., 2024), Interestingly, the scope of YOLOv8's applications extends beyond physical surveillance. Research by Amin et al. (2024) illustrates the model's usefulness in monitoring smoking-related content across social media platforms, showcasing its cross-domain versatility.

An important addition to the system is the integration of a Telegram-based alert mechanism, which consistently delivered notifications within an average response time of 1.5 seconds. This aligns with who emphasize the critical importance of timely responses in automated monitoring systems. Similarly, Zhu (n.d.) demonstrated YOLOv8's robustness in detecting small or partially visible objects, further reinforcing its suitability for crowded environments.

Despite its strengths, several limitations remain. The system's performance can be hindered in highly congested areas and relies heavily on stable internet connections for real-time notifications. To address these issues, (Lavu et al., 2024) propose leveraging edge computing and offline-capable notification systems, which could improve both reliability and independence from network conditions. Further support for YOLOv8's real-time capabilities comes from Rahman et al. (2024) who stress its advantages in fast-response scenarios.

From a societal perspective, the system contributes positively to public health by automating the detection of prohibited smoking behaviors and reducing the need for human surveillance. This aligns with the broader public health goals discussed by Yan Li et al. (2024). Nevertheless, ethical considerations regarding privacy and data protection must be carefully managed. As Liu et al. (2024), suggest, system developers should implement transparent operational policies and strong data security protocols to ensure responsible use.

In conclusion, the implementation of YOLOv8 in public space surveillance marks a meaningful step forward in the application of AI for regulatory and public health purposes. With continued development—especially in addressing current technical and ethical challenges—this system holds promise as a scalable, efficient, and socially acceptable tool for promoting healthier public environments.

Conclusion

This study successfully developed and implemented a YOLOv8-based monitoring system capable of detecting smoking activities in real time under various conditions, including low light and partial occlusion. The system achieved a high F1-Score of 81% and an accuracy of 89%, with an average notification delay of only 1.5 seconds via Telegram. These results demonstrate the system's potential as a technological support tool for enforcing public smoking bans. However, limitations remain, such as reduced detection accuracy in poor lighting and dependency on stable internet connectivity. Future research should explore improving detection in challenging conditions and expanding integration with other platforms or devices. This work contributes to public health efforts by offering a scalable and responsive solution to monitor and discourage smoking in public areas.

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Author Contributions

Conceptualization: S.AP, M and S; data curation: : S.AP, M and S funding acquisition: S.AP, M and S methodology: : S.AP, M and S visualization: : S.AP, M and S writing – original draft: : S.AP, M and S writing: : S.AP, M and S – review & editing: : S.AP, M and S.

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Conflicts of Interest

No Conflicts of interest.

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